Effects of Income on Life Expectancy and Other Health Disparities

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Abstract

A person's disposable income is often related to their ability to readily access healthcare and health-related resources. The relationship between income and mortality has historically been well established but not easily understood. This study attempts to bridge the gaps in understanding between wealth and mortality by revealing the relationship between income and life expectancy using cross-country data. This study also explores the relationships between life expectancy and other socioeconomic factors, such as the Gini coefficient, secondary education, healthcare expenditure, and healthcare access. A positive correlation has been hypothesized between the explanatory and dependent variable and is supported by regression analysis in this study.

I. Introduction

Our socioeconomic status is largely driven by our income, and even before we are born, the resources that will be available to us as children are determined by our parent's wealth. It effects where we live, what we eat, our education, our access to healthcare, and even our opportunities. It is important to understand the impact of socioeconomic status on standard of living and how that in turn affects our longevity.

One important factor that determines the availability of those resources is our disposable income. We must be able to take care of our basic needs such as shelter and food and then even more so by regularly seeing a physician and taking advantage of preventive care. When we are not able to take care of those basic needs it can detrimentally impact our ability to take care of our bodies long-term and lead to unforeseen disparities that could shorten our lives. Given one's resources and their ability to purchase medication and regularly see a physician, we can assume that someone who does not have the financial capabilities may not be able to take good care of their bodies. This paper explores the impact of income on life expectancy and other health disparities. Income is the primary independent variable, while life expectancy is the dependent variable.

II. Literature Review

A collaboration between the VCU Center on Society and Health and the Urban Institute (2015) researched the links between wealth and longevity and made some generalizations about the effects that income can have on life expectancy. The authors believe that the relationship between health and income is a gradient: one that is connected at every step of the economic ladder. Pulling from US national data, they found that people with lower incomes reported poorer health and higher risk of disease. Families at the federal poverty level (FPL in 2014 was $23,850 for a family of four) are five times more likely have reported being in fair or poor health and three times more likely to have reported physical limitations due to chronic illness compared to those with incomes at or above 400% of the poverty level. Lower income Americans are at greater risk for heart disease, diabetes, stroke and other chronic disorders. Children living in households at the FPL are at greater risk for childhood asthma, heart conditions, and childhood obesity. The study links their likeliness to have one or more of these diseases to their ability to afford healthcare services, health insurance, and healthier lifestyles.

To better understand the empirical relationship between income and life expectancy, Chetty et al. (2016) conducted a study of life expectancy across geographic variations and income groups in the US from 2001-2014. Their objective was to measure the level, time trend, and geographic variation between income and life expectancy using deidentified tax records and Social Security Administration death records. They collected data on 1.4 billion individuals and used the tax records to establish a person's pre-tax earnings as a measure of income; these records were randomly selected within specific geographic regions of the US. The authors then conducted regression analysis to understand the correlations in the data. They found that "higher income was associated with greater longevity" across all income groups. The gap in life expectancy between the richest 1% and poorest 1% was 14.6 years for men and 10.1 years for women (95% CI). They also found that this inequality gap increased over time in the data; between 2001 and 2014, the top 5% saw an increase of 2.34 years for men and 2.91 years for women, but for the bottom 5% there was an increase of only 0.32 years for men and 0.04 years for women (99% CI). The data also provided evidence that there were substantial geographic differences and that these differences were correlated with health behaviors (e.g. smoking, $r = -0.69$ at 99% CI) but not significantly correlated with healthcare access, environmental factors, income inequality, or labor market conditions. For lower income groups, local characteristics such as percentage of immigrants ($r=0.72$, $p<0.01$), percentage of college graduates ($r=0.42, p<0.01$), and government expenditures ($r=0.57, p<0.01$) were positively correlated with life expectancy.

A study conducted in Norway compared the association of household income with life expectancy and cause-specific mortality rates from 2005-2015 to the US data found in the previous model. Authors Kinge, Modalsi, and Overland (2019) thought this would be an interesting comparison because of the large differences in healthcare systems between the two countries: Norway having a tax-financed universal health care system and the US having a largely private-based insurance run system. They used regression models to measure the life expectancy at 40 years of age and cause-specific mortality rates and then used those estimations to compare with data from the US. Their findings were that the life expectancy for women was highest in the top 1% of income groups (86.4 years, 95% CI), which was 8.4 years longer than the life expectancy for women in the lowest 1% of income. Similarly for men, the top 1% had an expected 84.4 years, while the bottom 1% had 70.6 years (both 95% CI). They also found that life expectancy for women in the highest quartile increased by 3.2 years (95% CI) and 3.1 years (95% CI) for men, while the lowest income quartile saw a decrease of 0.4 years (95% CI) for women and an increase of 0.9 years (95% CI) for men. Cause-specific rates were seen to increase among non-communicable diseases, defined as chronic conditions that do not result from infectious diseases.

Specifically, there was a rise in deaths from cardiovascular disease, cancer, pulmonary disease, and dementia in older age groups, as well as an increase in deaths from substance abuse and suicide in younger age groups. The authors attribute some of the differences in life expectancy to the increase in overall disease rates and found these results to be similar to trends in the US, drawing conclusions that the design of the healthcare system in each country is not a significant contributor to these findings, but that there is a strong, positive correlation between income quartiles and overall life expectancy.

In another case study, Rasella, Aquino, and Baretta (2013) measured the impact of income inequality on life expectancy in Brazil. They felt it was important to consider this relationship in a developing economy, where people are more susceptible to the impacts of rapid growth. These increasing rates of output can create even larger income gaps between the highest and lowest income groups than they would in a post-development country. Their regression analysis considered life expectancy as the dependent variable and the Gini coefficient as the explanatory variable across 27 member-states. They were also able to control for other variables that have been recognized in the literature as being determinants of life expectancy, such as secondary education achievement, insurance coverage by the National Health System in Brazil, number of hospital beds per 1,000 inhabitants, and total expenditure on health as a percentage of GDP. The results found that there was a negative association between the Gini index and life expectancy, which proved to be statistically significant at the 5% level even after adding in socioeconomic and health-related variables in multiple models. They conclude that due to this correlation, people of the top 10% and 20% income groups have similar health conditions and as we move towards lower income levels, income has a substantially stronger effect on overall health, and therefore life expectancy.

III. Data

In order to define the relationship between income and life expectancy, cross-sectional data was collected across 200+ countries. The dependent variable used was life expectancy, defined as the average total years of an adult, and is the most frequently used statistic to measure longevity. The primary explanatory variable studied was the natural logarithm of GDP per capita. This variable was chosen because it is often used to measure the average level of national income per person and gives a dollar value to the average standard of living; inflation is held constant, so that GDP per capita accurately reflects the real growth in output of the economy. GDP per capita is also commonly used for cross-country comparison which makes it a practical indicator for this study. All the gathered data for these variables was sourced from the World Bank for 2015. In Figure 1, there is a strong, positive correlation (r=0.83) between the natural logarithm of GDP per capita and total life expectancy.

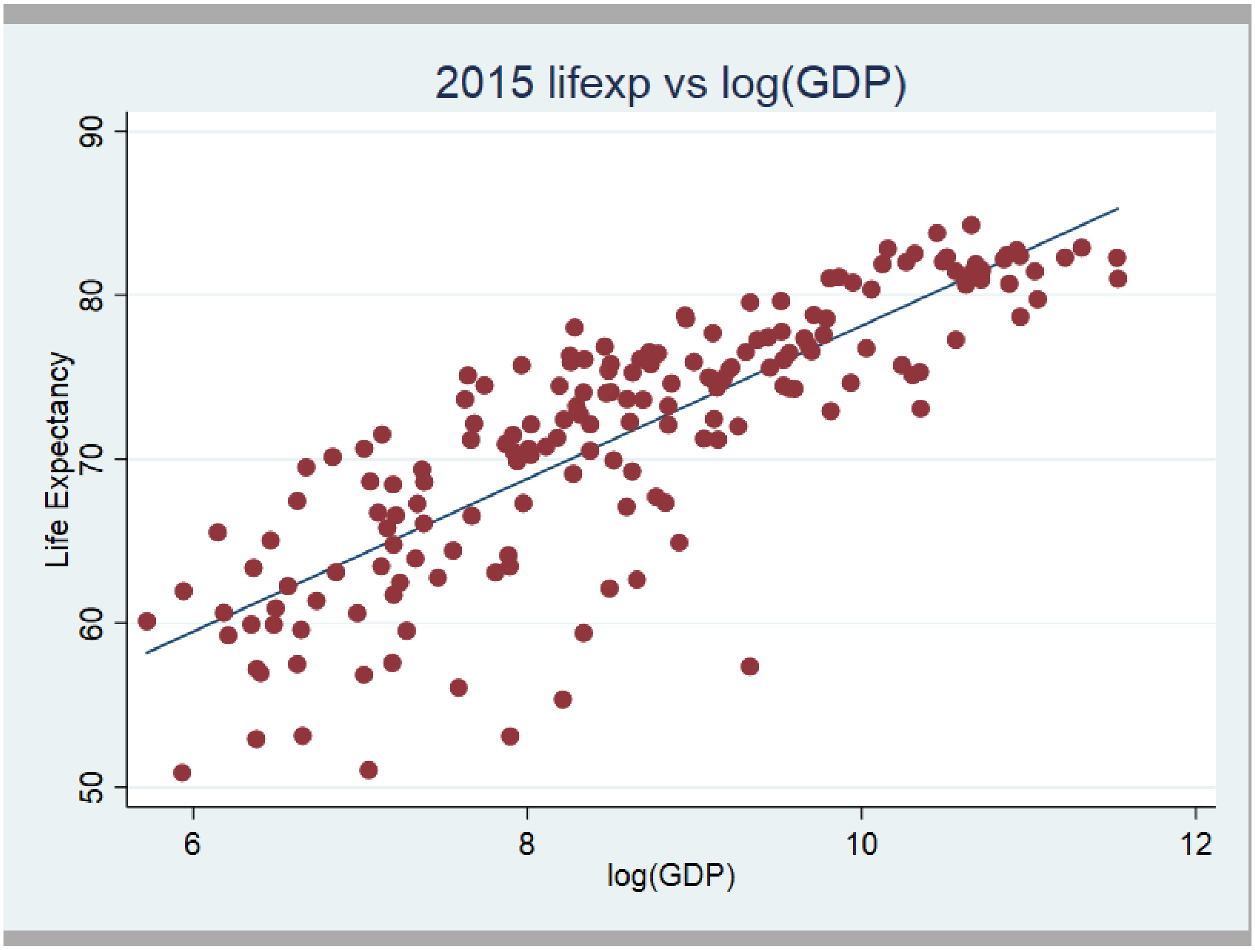

Figure 1. Scatterplot of Life Expectancy vs Log(GDP)

Additionally, there were several other explanatory variables selected for the multiple regression models to uncover the ceteris paribus effect of GDP per capita on life expectancy. These variables include the natural logarithm of population, Gini index, poverty head-count ratio, education, total health expenditure as a percentage of GDP, number of doctors per 1,000 people, and percentage of deaths caused by non-communicable disease. Data for population, Gini index, poverty head-count ratio, health expenditure, number of doctors, and deaths due to non-communicable disease was collected from the World Bank for 2015. Data on education is also from 2015 was collected from the Global Change Data Lab ran by the University of Oxford. The population data records the number of people within a country, and the natural logarithm was taken to scale down very large populations (millions) to create a more linear regression. Countries with larger populations tend to have larger values of GDP, which has been assumed to have a positive correlation with life expectancy. The Gini index measures the income distribution in a country using a value between 0% and 100%, 0% = perfect income equality and 100% = perfect income inequality. A high Gini index values indicates that those who make higher incomes also receive a larger proportion of total income of the population, meaning that a smaller percentage of people hold more of the wealth in a country. This variable is predicted to have a negative association with life expectancy, as income inequality increases it leads to a decrease in total life expectancy. The poverty headcount ratio represents the percentage of a country's population living at or below the international extreme poverty line of $1.90/day (adjusted for purchasing power parity). It is predicted to be negatively associated with life expectancy as more of the population lives in poverty, the average life expectancy decreases. Poverty levels are directly related to income levels and have a large impact on a person's ability to afford health-related services as well as their ability to secure basic human needs such as food and housing. Education is calculated as the average years of schooling among the population and is thought to have a positive relationship with life expectancy. This is due to education's strong association with income, finding that those with higher levels of education also have higher incomes and is therefore linked to their socioeconomic status. Health expenditure is given as a percentage of GDP and is predicted to be positively associated with life expectancy. The more a country invests in healthcare the more likely people will have increased access to services needed to improve their personal health. The number of doctors per 1,000 people represents doctor accessibility and timeliness in the case of an emergency. This is thought to have a positive association with life expectancy as the more trained doctors a country has, the increase in chances that a person might schedule regular checkups and be attended to in emergency situations. Lastly, the percentage of non-communicable disease-related deaths measures the ratio of non-communicable causes to other causes of death. Non-communicable disease deaths have a negative correlation with access to preventive care, nutrition, and healthy social behaviors. This variable is expected to have a negative association with life expectancy given that living with this type of disease has an adverse effect on quality of health and longevity. A summary of each variable can be found in Table 1.

Table 1 – Variable Descriptions

Variable Name	Description	Units	Year	Source
lifexp	Avg total expected years	Years	2015	World Bank
log(GDP)	Natural log of GDP	Constant dollars	2015	World Bank

	per capita	(USD)		
log(pop)	Natural log of total population	# of people	2015	World Bank
gini	Gini coefficient- measures income inequality	Value btw 0 and 100, 0=perfect equality, 100=perfect inequality	2015	World Bank
pov	Poverty head-count ratio- % of population living at or below poverty line of $1.90/day	Percentage	2015	WorldBank
educ	Average years of schooling	Years	2015	UNDC
healthexp	Total health expenditure as a percentage of GDP	Percentage	2015	WorldBank
doc	# doctors per 1,000 people		2015	WorldBank
ncd	% deaths of population caused by non-communicable diseases	Percentage	2015	WorldBank

Descriptive statistics for each variable can be found below in Table 2.

Table 2 – Variable Descriptive Statistics

Variable	Observations	Mean	Std Dev.	Min.	Max.
lifexp	181	71.67	7.91	50.9	84.3
log(GDP)	184	8.62	1.39	5.72	11.53
log(pop)	184	15.70	2.04	10.84	21.04
gini	81	36.92	7.84	25.4	59.1
pov	81	5.15	11.59	0	58.7
educ	182	8.43	3.12	1.4	14.1
healthexp	178	6.56	2.80	1.82	20.41
doc	104	2.13	1.57	.03	7.78
ncd	178	69.06	21.45	25.28	95.34

Though most of the variables have a large number of observations, those that do not will reduce the sample size for the later regression models. This is due to data being unavailable or unreported for a specific country at the time of the collection or during the period of observation (2015).

Before continuing to the regression models, it is necessary to review the Gauss-Markov conditions for linear regressions. The assumptions are as follows:

1. Model is linear in parameters such that: $y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + u$, where all β terms are the unknown parameters of interest and u is the error term. All models in this study satisfy this assumption, as all explanatory variables are linearly related.
2. Data is obtained by random sampling: Data was obtained from all countries where data was available for the given period, so there were no exclusions from the sample, therefore the sample can be considered random.
3. No perfect collinearity between explanatory variables: STATA was utilized to check explanatory variables for collinearity and no exact linear relationships were found, therefore the condition is met (see Appendix B).
4. Zero conditional mean: The expected value of the error term cannot be assumed as zero as there could be unaccounted factors in u that affect life expectancy. All results from this study should be interpreted with caution.
5. Homoskedasticity: The variance of the error term cannot be verified therefore this assumption is difficult to assume. Unexpected variables in the error term could influence the variance. All results from this study should be interpreted with caution.

IV. Results

After confirming all five Gauss-Markov conditions, several regression models were used to test the hypothesis. All STATA regression results can be found in Appendix C.

Model 1:

First, a simple linear regression model is formulated to test the relationship between the natural logarithm of GDP per capita and life expectancy. The model is written as:

$$lifexp = \beta_0 + \beta_1(logGNI)$$

This model has a sample size of 181 countries. From the STATA output, the estimated regression model can be written as:

$$lifexp = 31.53 + 4.66(logGDP)$$

The model has an R-squared value of 0.68, suggesting a moderately strong correlation between life expectancy and GDP per capita. The coefficient on *logGDP* has a positive sign as predicted, indicating there is a positive relationship between life expectancy and GDP per capita. Since this is a level-log model, the regression can be interpreted as a 1% increase in GDP per capita has a 4.66 year increase in life expectancy.

Though constructing a simple regression model confirms our predictions on the likely relationship between the independent and dependent variable, going further to test a multiple linear regression will provide a more accurate result. By adding explanatory variables, it can help explain the variation in the dependent variable and hold important factors constant to uncover the ceteris paribus effect in this study.

Model 2:

This is a multiple regression model computed by adding in all secondary explanatory variables to reveal their potential significance in the study. The model is written as:

$$\begin{aligned} lifexp = \beta_0 + \beta_1(logGDP) + \beta_2(gini) + \beta_3(pov) + \beta_4(educ) + \beta_5(healthexp) + \beta_6(doc) \\ + \beta_7(ncd) + \beta_8(logpop) + u \end{aligned}$$

This model has a sample size of 55 countries, which is relatively small compared to the first model. This is due to the limited data available on the poverty headcount ratio, Gini index, and number of doctors. A small sample size can lead to micronumerosity, but given that all the explanatory variables have an effect on life expectancy, I will continue with the regression analysis, keeping this in mind. After STATA output, the estimated equation can be written as:

$$\begin{aligned} lifexp = 39.760 + 3.528(logGDP) + .055(gini) - .099(pov) - .834(educ) + .328(healthexp) \\ - 0.008(doc) + .149(ncd) - .248(logpop) \end{aligned}$$

The model has an R-squared value of 0.92 denoting a very strong correlation between life expectancy and GDP per capita. The coefficient on *logGDP* has a positive sign as predicted, showing the positive relationship between GDP per capita and life expectancy. The coefficient in this model is significantly smaller which is expected due to the simple regression model overestimating the impact of the explanatory variable on the dependent variable. This is due to omitted variable bias, and by including additional explanatory variables in this model, I can better explain some of variance. The coefficient of *logGDP* can be interpreted as a 1% increase in GDP per capita results in a 3.528 year increase in life expectancy. An unexpected result of the model is that *educ* has a negative coefficient, meaning that an increase in average years of schooling decreases a person's life expectancy by -.834. Another unexpected result is the positive coefficient on *gini,* meaning an increase in the Gini index, increases the overall life expectancy in a country. This could be due to the massive differences in healthcare quality between income groups, with higher income groups amassing more wealth and leading to the positive outcome here. Additionally, the coefficient on *doc* is negative meaning that an increase in 1 doctor per 1,000 people decreases life expectancy by -0.008 years. This result is the opposite of my prediction, however, both *gini* and *doc* had t-values that did not prove to be statistically significant, so they will be removed for Model 3 and considered in an extension of this study.

Model 3:

This model removes the variables from Model 2 that were not statistically significant at the 10% level. The new model can be written as:

$$lifexp = \beta_0 + \beta_1(logGDP) + \beta_2(pov) + \beta_3(educ) + \beta_4(healthexp) + \beta_5(ncd) + \beta_6(logpop) + u$$

This model has a sample size of 80 countries, which is higher than the sample in Model 2. After performing the STATA regression, the estimated equation can be written as:

$$lifexp = 37.91 + 2.97(logGDP) - 0.033(pov) - 0.649(educ) + 0.249(healthexp) + 0.199(ncd) - 0.047(logpop)$$

This model has an R-squared value of 0.89, again confirming a strong correlation between life expectancy and GDP per capita. The coefficient on *logGDP* can be interpreted as a 1% increase in a country's GDP per capita results in a 2.97 increase in total life expectancy. Countries could possibly consider these results in policy applications, that economic growth can lead to positive impacts on overall health. The coefficient on *educ* is still negative, which is the opposite of my prediction. This could be because personal investment in education could cause someone to forego income, and the net present value of their earnings after completion of education may be lower over the course of their lifetime than working during those same years. It could also be due to people having constrained disposable incomes, and spending money on education means spending less money in other areas that may have a greater return and impact on their longevity. The coefficient on *ncd* is also the opposite of my prediction, but this could be the result of increased research and development spending in the medical field, leading to better treatment plans that helps prolong one's life expectancy after diagnosis. I would be interested in comparing this result with the percentage of communicable disease (infectious disease) deaths to see how that variable might have a different impact on life expectancy and will explore this further in the extension model.

Table 3 provides a summary of the estimation results for the three linear regression models.

Table 3 – Regression Model Estimation Results

Dependent Variable: *lifexp*			
Independent Variables	Model 1	Model 2	Model 3
loggdp	4.66*** (.238)	3.53*** (.301)	2.99*** (.32)
gini	--	.055 (.042)	--
pov	--	-.099** (.043)	-.033 (.036)
educ	--	-.834*** (.191)	-.649*** (.184)
healthexp	--	.328*** (.113)	.249* (.128)
doc	--	-.008 (.256)	--
ncd	--	.149*** (.035)	.199*** (.033)
logpop	--	-.248* (.129)	-.047 (.15)
Intercept	31.53*** (2.07)	39.76*** (3.91)	37.91*** (3.73)
Number of Observations	181	55	80
R-Squared	0.68	0.92	0.89

*Statistically significant at ***1%, **5%, *10%

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Appendix

Appendix A. List of countries used in study.

Afghanistan	China	Haiti	Mauritania	Serbia
Albania	Colombia	Honduras	Mauritius	Seychelles
Algeria	Comoros	Hong Kong SAR	Mexico	Sierra Leone
Angola	Congo, Dem. Rep.	Hungary	Micronesia.	Singapore
Antigua and Barbuda	Congo, Rep.	Iceland	Moldova	Slovak Republic
Argentina	Costa Rica	India	Mongolia	Slovenia
Armenia	Cote d'Ivoire	Indonesia	Montenegro	Solomon Islands
Aruba	Croatia	Iran	Morocco	South Africa
Australia	Cuba	Iraq	Mozambique	South Sudan
Austria	Cyprus	Ireland	Myanmar	Spain
Azerbaijan	Czech Republic	Israel	Namibia	Sri Lanka
Bahamas	Denmark	Italy	Nepal	St. Kitts and Nevis
Bahrain	Djibouti	Jamaica	Netherlands	St. Lucia
Bangladesh	Dominica	Japan	New Zealand	St. Vincent
Barbados	Dominican Republic	Jordan	Nicaragua	Sudan
Belarus	Ecuador	Kazakhstan	Niger	Suriname
Belgium	Egypt, Arab Rep.	Kenya	Nigeria	Sweden
Belize	El Salvador	Kiribati	North Macedonia	Switzerland
Benin	Equatorial Guinea	Korea, Rep.	Norway	Tajikistan
Bermuda	Estonia	Kuwait	Oman	Tanzania
Bhutan	Eswatini	Kyrgyz Republic	Pakistan	Thailand
Bolivia	Ethiopia	Lao PDR	Panama	Timor-Leste
Bosnia and Herzegovina	Fiji	Latvia	Papua New Guinea	Togo
Botswana	Finland	Lebanon	Paraguay	Tonga
Brazil	France	Lesotho	Peru	Trinidad and Tobago
Brunei Darussalam	Gabon	Liberia	Philippines	Tunisia
Bulgaria	Gambia	Libya	Poland	Turkey
Burkina Faso	Georgia	Lithuania	Portugal	Turkmenistan
Burundi	Germany	Luxembourg	Qatar	Uganda
Cabo Verde	Ghana	Madagascar	Romania	Ukraine
Cambodia	Greece	Malawi	Russia	United Arab Emirates
Cameroon	Grenada	Malaysia	Rwanda	United Kingdom
Canada	Guatemala	Maldives	Samoa	United States
Central African Republic	Guinea	Mali	Sao Tome	Uruguay
Chad	Guinea-Bissau	Malta	Saudi Arabia	Uzbekistan
Chile	Guyana	Marshall Islands	Senegal	Vanuatu
				Vietnam
				Yemen
				Zambia
				Zimbabwe

Appendix B. Correlation coefficients between each variable to fulfill Gauss-Markov assumption 3:

	lifexp	*loggdp*	*logpop*	*gini*	*pov*	*educ*	*healthexp*	*doc*	*ncd*
lifexp	1.00								
loggdp	0.9120	1.00							
logpop	-0.0844	-0.0851	1.00						
gini	-0.2999	-0.3905	0.2934	1.00					
pov	-0.6117	-0.5192	-0.0386	0.3088	1.00				
educ	0.6487	0.7498	-0.1965	-0.4922	-0.4772	1.00			
healthexp	0.6041	0.6171	0.0059	-0.2057	-0.1705	0.5935	1.00		
doc	0.5479	0.5843	-0.2322	-0.4458	-0.3792	0.7518	0.4748	1.00	
ncd	0.7132	0.6442	-0.0912	-0.3900	-0.6515	0.7933	0.4372	0.6925	1.00

Appendix C. STATA Regression Model Outputs

Model 1:

```
. regress lifexp loggdp

      Source |       SS           df       MS      Number of obs   =       181
-------------+----------------------------------   F(1, 179)       =    384.83
       Model |  7685.21016         1  7685.21016   Prob > F        =    0.0000
    Residual |  3574.74241       179   19.970628   R-squared       =    0.6825
-------------+----------------------------------   Adj R-squared   =    0.6808
       Total |  11259.9526       180  62.5552921   Root MSE        =    4.4689

------------------------------------------------------------------------------
      lifexp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      loggdp |   4.661511   .2376264    19.62   0.000     4.192602    5.130421
       _cons |    31.5251   2.073444    15.20   0.000     27.43356    35.61663
------------------------------------------------------------------------------
```

Model 2:

```
. regress lifexp loggdp gini pov educ healthexp docper1000 ncd logpop
```

Source	SS	df	MS
Model	1279.46782	8	159.933477
Residual	110.103831	46	2.39356153
Total	1389.57165	54	25.7328083

Number of obs	=	55
$F(8, 46)$	=	66.82
Prob > F	=	0.0000
R-squared	=	0.9208
Adj R-squared	=	0.9070
Root MSE	=	1.5471

lifexp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
loggdp	3.527895	.3012786	11.71	0.000	2.921452	4.134337
gini	.0553388	.042306	1.31	0.197	-.0298188	.1404963
pov	-.0997248	.0431755	-2.31	0.025	-.1866325	-.012817
educ	-.8342373	.1907474	-4.37	0.000	-1.218192	-.4502827
healthexp	.327726	.113286	2.89	0.006	.0996931	.5557588
docper1000	-.0088447	.2559463	-0.03	0.973	-.524038	.5063485
ncd	.1486393	.034654	4.29	0.000	.0788844	.2183941
logpop	-.2479485	.129316	-1.92	0.061	-.5082482	.0123512
_cons	39.75976	3.907033	10.18	0.000	31.89531	47.62421

Model 3:

```
. regress lifexp loggdp pov educ healthexp ncd logpop
```

Source	SS	df	MS
Model	2716.26176	6	452.710294
Residual	349.590868	73	4.788916
Total	3065.85263	79	38.8082611

Number of obs	=	80
$F(6, 73)$	=	94.53
Prob > F	=	0.0000
R-squared	=	0.8860
Adj R-squared	=	0.8766
Root MSE	=	2.1884

lifexp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
loggdp	2.968974	.3196731	9.29	0.000	2.331866	3.606081
pov	-.0327965	.035929	-0.91	0.364	-.1044028	.0388099
educ	-.6486024	.1838291	-3.53	0.001	-1.014973	-.2822315
healthexp	.249425	.1279135	1.95	0.055	-.0055063	.5043563
ncd	.1985595	.0326528	6.08	0.000	.1334826	.2636365
logpop	-.0471936	.1499812	-0.31	0.754	-.3461057	.2517184
_cons	37.90689	3.730009	10.16	0.000	30.47299	45.34078